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Testing for asymmetries in the predictive model for oil price-inflation nexus

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Abstract

In this paper, we test whether accounting for asymmetries matters in inflation forecasting. Using OECD data, we find that such consideration does little to improve the forecast performance of oil price in the predictive model for inflation. Overall, we find evidence in favour of asymmetries for the in-sample analyses while the symmetric variant performs better for the out-of-sample forecast.

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1. Introduction

In a recent study by Salisu et al. (2017), the role of asymmetries is captured in the analyses of the relationship between oil price and inflation. Among other things, the paper argues for the consideration of oil price asymmetries in the estimation process regardless of whether the country is a net oil exporter or net oil importer. However, the analyses in the paper are restricted to in-sample estimation the outcome of which may not be entirely valid for the out-of-sample forecast of the estimated model. In this paper, we further extend the Salisu et al. (2017) to test whether the consideration of oil price asymmetries matters in the out-of-sample forecast of the predictive model for oil price-inflation nexus.

Despite the importance of accurate inflation forecasts to the design and effectiveness of stabilization policies – especially monetary policy, it has become a herculean task to derive such forecasts by policymakers and other professionals. Although, the literature is replete with different predictors of inflation, the increasing evidence in favour of oil price has continued to gain prominence.[1] Two strands of the extant literature in this regard have suggested a plausible way of improving inflation forecasts via oil price. The first strand is the growing consensus that changes in global oil prices matter for understanding inflation dynamics, at least in the short run (see Salisu et al., 2017 for a review). Some of these studies show that incorporating energy prices or crude oil prices into the Phillips curve based inflation models improves their forecast performance (see Chen et al., 2014 and Salisu et al., 2017). The second strand of the literature, though currently scanty, suggests that the effect of changes in oil prices on inflation could be asymmetry and non-linear (see Hooker, 2002 and Salisu et al., 2017).

Thus, in this paper, we further test whether accounting for these asymmetries will enhance inflation forecast. Our contribution to the literature is two-fold. First, we investigate the role of oil price asymmetries in inflation forecasting. While a number of previous studies forecast inflation using non-linear models (see Moshiri and Cameron, 2000; Ascari and Marrocu, 2003; and Marcellino, 2008), to our knowledge, none has paid attention to the role of oil price asymmetries. Second, following Salisu et al. (2017,b) which find that augmenting the traditional output-gap Phillips curve model with oil prices provides better inflation forecasts than other variants, we adopt this model as our benchmark model. In addition, augmenting the traditional Phillips curve in this way allows for both the demand-and supply-side in inflation forecasting.

The rest of the paper is structured as follows: Section 2 provides motivation for the study. Section 3 set up the model including the forecast performance measures and data issues. In Section 4, we present and discuss the results while Section 5 concludes the paper.

2. Motivation for the Study

Following the major oil price shocks of the 1970s and the subsequent attempts by Hamilton (1983, 2003) to unravel its macroeconomic consequence, a number of studies have since established a link between changes in oil price and macroeconomic fundamentals such as output (see Hamilton, 2003; Barsky and Kilian, 2004; Kilian and Vigfusson, 2013; Bashar et al., 2013; Morana, 2017 for a review), inflation/domestic prices (see Baumeister and Kilian, 2014; Dedeoğlu and Kaya, 2014; Salisu et al., 2017), stock price (Jones and Kaul, 1996; Park and Ratti, 2008; Kumar et al., 2012; Managi and Okimoto, 2013; Narayan and Gupta, 2014;

[1] Coibion and Gorodnichencko (2015) also note that, contrary to expectations, inflation rate increased during the financial crisis era and the increase was driven largely by increase in oil prices.

Salisu and Oloko, 2015; Devpura et al., 2017; Salisu and Isah, 2017) and exchange rate (see Ahmad and Hernandez, 2013; Atems et al., 2015; Bal and Rath, 2015; Chou and Tseng, 2015; Jiang and Gu, 2016), among others. Thus, in this study, we augment the Phillips curve based inflation model with oil price and thereafter we test its predictability in producing accurate inflation forecasts. The proposed revision to Phillips curve allows us to capture both the demand side (demand-pull inflation) and supply side (cost-push inflation) in the predictive model for inflation. The literature is quite replete with the application of the traditional Phillips curve in modeling inflation (see for example, Stock and Watson, 2003, 2007, 2008; Canova, 2007; Ang et al., 2007; Riggi and Venditti, 2015; Salisu et al., 2017)

Another issue of interest when modelling with oil price is the need to allow for nonlinearities in form of asymmetric oil price changes. This approach to oil modeling became pronounced by Hamilton (2003) who made the case that the predictive relationship between oil prices and U.S. real GDP is nonlinear (see also Kilian and Vigfusson, 2011; Kilian and Vigfusson, 2013). Recent papers have also suggested similar evidence of nonlinear (asymmetric) relationship between oil price and stock returns (see Narayan and Gupta, 2014; Bannigidadmath and Narayan, 2015; Narayan and Bannigidadmath, 2015; Devpura et al., 2017); oil price and exchange rate (see Ahmad and Hernandez, 2013; Atems et al., 2015; Bal and Rath, 2015; Chou and Tseng, 2015; Jiang and Gu, 2016) and oil and inflation (see Leblanc and Chinn, 2004 and Salisu et al., 2017). However, most of these studies including inflation are restricted to in-sample analyses while the out-of-sample forecast has received very little attention in the literature. Thus, we extend the literature on oil price-inflation nexus in order to test whether allowing for nonlinearities (asymmetries) will enhance both the in-sample and out-of-sample forecast results for inflation.

3. The Model and Data

We adopt the augmented Phillips curve model as in Salisu et al. (2017) and both the symmetric and asymmetric variants are considered. The former case is the benchmark model and it assumes identical effects of oil price on inflation as given below:

$$\pi_t = \alpha + \lambda \overline{g}_t + \gamma p_t + \varepsilon_t \tag{1}$$

where π_t is the inflation rate computed as $\log(cpi_t / cpi_{t-1})$, $\overline{g}_t$ denotes output-gap calculated as $\log(y_t / \overline{y}_t)$ such that y_t is the actual output proxied by real GDP and $\overline{y}_t$ is the potential output (or potential real GDP) that is measured using the Hodrick Prescott filter, while p_t measures changes in global crude oil price computed as $\log\left(oil\ price_t / oil\ price_{t-1}\right)$. Note that $\overline{g}_t$ and p_t capture the demand- and supply-side of inflation respectively. For the asymmetric variant, we disaggregate p_t in equation (1) into positive (p^+) and negative (p^-) oil price changes as expressed below:

$$\pi_t = \alpha + \lambda \overline{g}_t + \gamma^+ p_t^+ + \gamma^- p_t^- + \varepsilon_t \tag{2}$$

The decomposition of p_t into p^+ and p^- follows the approach proposed by Shin et al. (2014) which is considered to have computational advantages over the dummy variable approach (see Van Hoang et al., 2016). The p^+ and p^- are defined theoretically as:

$$p_t^+ = \sum_{j=1}^{t} \Delta p_j^+ = \sum_{j=1}^{t} \max\left(\Delta p_j, 0\right) \tag{3a}$$

$$p_t^- = \sum_{j=1}^{t} \Delta p_j^- = \sum_{j=1}^{t} \min\left(\Delta p_j, 0\right) \tag{3b}$$

In order to exploit more useful dynamics in our model, we express equations (1) and (2) in autoregressive distributed lag (ARDL) model (see equations (4a) and (4b)). The equation (4b) is usually described as a nonlinear (asymmetric) ARDL model due to the disaggregated oil price (see Shin et al., 2014). Van Hoang et al. (2016) also document the various advantages of modelling inflation with the ARDL approach.

$$\pi_t = \alpha + \sum_{i=1}^{p} \delta_i \pi_{t-i} + \sum_{j=0}^{q} \lambda_j \overline{g}_{t-j} + \sum_{j=0}^{q} \gamma_j p_{t-j} + \varepsilon_t \tag{4a}$$

$$\pi_t = \alpha + \sum_{i=1}^{p} \delta_i \pi_{t-i} + \sum_{j=0}^{q} \lambda_j \overline{g}_{t-j} + \sum_{j=0}^{q} (\gamma_j^+ p_{j,t-j}^+ + \gamma_j^- p_{j,t-j}^-) + \varepsilon_t \tag{4b}$$

For completeness, we also consider an autoregressive model with drift $\left(\pi_t = \alpha + \rho\pi_{t-1} + \varepsilon_t\right)$. To examine the predictive ability of the relevant equations specified, we employ the Adjusted Root Mean Square Error (ARMSE) developed by Moosa and Burns (2012). This approach takes into account the ability of the model to predict the direction of change in addition to the magnitude of error captured by the conventional RMSE. Moosa and Burns (2012) demonstrate that the ARMSE is not biased towards measures of either magnitude (RMSE) or direction (CR). The forecast period is divided into two – in-sample forecast period and out-of-sample forecast period. The in-sample forecast covers the estimation period (2000q1 – 2010q4) while the latter is for the remaining period (2011q1 – 2016q4). Thereafter, we compute the Adjusted Root Mean Square Error (ARMSE) for both the in-sample and out-of-sample forecasts. The ARMSE can be calculated as follows:

In-Sample: $$ARMSE = \sqrt{\frac{CR}{m} \sum_{t=1}^{m} \left(\hat{\pi}_t - \pi_t\right)^2} \tag{5a}$$

Out-of-Sample: $$ARMSE = \sqrt{\frac{CR}{k} \sum_{t=1}^{k} \left(\hat{\pi}_t - \pi_t\right)^2} \tag{5b}$$

where CR is the confusion rate computed as $CR = 1 - DA$, and DA which is the direction accuracy is calculated correspondingly for the in-sample and out-of-sample as:

In-Sample: $$DA = \frac{1}{m} \sum_{t=1}^{m} a_t \tag{6a}$$

Out-of-Sample: $$DA = \frac{1}{k} \sum_{t=1}^{k} a_t \tag{6b}$$

where $a = \begin{cases} 1 \\ 0 \end{cases} if \begin{cases} \left(\hat{\pi}_{t+1} - \pi_t\right)\left(\pi_{t+1} - \pi_t\right) > 0 \\ \left(\hat{\pi}_{t+1} - \pi_t\right)\left(\pi_{t+1} - \pi_t\right) < 0 \end{cases}$.

If two models have equal RMSEs, the model with a higher *CR* should have a higher ARMSE (Moosa and Burns, 2012).

We use quarterly data for the 35 Organization for Economic Co-operation and Development (OECD) member countries for the period 2000:Q1 to 2016:Q4. CPI Indices and GDP data were obtained from the OECD Statistics Database while crude oil prices (Brent) is downloaded from the US Energy Information Administration (US-EIA) website.

4. Results and Discussions

In Table I, we present the frequency distribution of the forecast performance for all the relevant models derived from the ARMSE statistics reported in Table III. Models with lower ARMSE values have better inflation forecast performance and are in bold fonts in Table III. Also, the forecast performance of the asymmetric variant and the autoregressive models relative to the benchmark model is presented in Table II.

Three major results are noteworthy. First, the asymmetric model variants often outperform the symmetric ones in terms of in-sample inflation forecast performance. Second, the symmetric model variants provide more accurate out-of-sample inflation forecasts for most countries in the OECD. The conclusion remains the same irrespective of whether the forecasts are for four-quarter ahead or eight-quarter ahead. This suggests that the symmetric variant is more appropriate for inflation forecasting with oil while the asymmetric version is suitable for impact analyses. Third, both variants outperform the autoregressive model; in other words, any autoregressive model that ignores the demand-and supply-side of inflation may produce less desirable results.

Table I: Frequency distribution of forecast performance

In-Sample Forecast			
	Autoregressive	**APC-Without Asymmetry**	**APC-With Asymmetry**
Autoregressive	-		
APC-Without Asymmetry	30:3	-	
APC-With Asymmetry	30:3	18:9	-
Out-of-Sample Forecast for $k = 4$			
Autoregressive	-		
APC-Without Asymmetry	20:5	-	
APC-With Asymmetry	15:12	13:15	-
Out-of-Sample Forecast for $k = 8$			
Autoregressive	-		
APC-Without Asymmetry	27:7	-	
APC-With Asymmetry	17:18	7:25	-

Note: Suppose we represent each cell with a:b; a is for the row while b is for the column. Each cell captures the number of times each row outperforms the corresponding column and vice versa. APC denotes augmented Phillips curve.

Table II: Percentage comparison with the Benchmark model

	APC-With Asymmetry	Autoregressive
In-sample	$\uparrow$ 100%	$\downarrow$ 90%
Out-of-Sample $(k=4)$	$\downarrow$ 13%	$\downarrow$ 75%
Out-of-Sample $(k=8)$	$\downarrow$ 72%	$\downarrow$ 74%

Note: $\downarrow$ and $\uparrow$ represent percentage decrease and increase relative to the benchmark model respectively.

Table III: Inflation forecast performance using ARMSE

Country	In-Sample Forecast			Out-of –Sample Forecast					
	Autoregressive	**Symmetry Phillips Curve**	**Asymmetry Phillips Curve**	**Autoregressive**		**Symmetry Phillips Curve**		**Asymmetry Phillips Curve**	
				$k=4$	$k=8$	$k=4$	$k=8$	$k=4$	$k=8$
Australia	0.002	0.002	**0.001**	0.002	0.002	**0.000**	**0.001**	0.000	0.004
Austria	0.002	0.001	**0.001**	0.000	0.002	0.000	0.001	**0.000**	**0.001**
Belgium	0.002	**0.001**	0.001	0.000	0.001	**0.000**	**0.001**	0.002	0.003
Canada	0.003	0.001	0.001	0.002	0.002	**0.000**	**0.001**	0.000	0.001
Chile	0.003	**0.002**	0.003	0.002	0.002	**0.007**	**0.007**	0.011	0.013
Czech	0.003	0.002	**0.002**	0.003	0.002	0.003	**0.003**	**0.002**	0.004
Denmark	0.002	0.001	**0.001**	0.002	0.002	0.001	0.002	**0.001**	**0.001**
Estonia	0.004	**0.003**	0.003	0.005	0.006	**0.003**	**0.004**	0.006	0.013
Finland	0.002	0.001	**0.001**	0.002	0.002	**0.000**	**0.001**	0.001	0.002
France	0.002	**0.001**	0.001	0.000	0.002	0.000	0.001	**0.000**	**0.001**
Germany	0.001	0.001	**0.001**	0.002	0.002	0.001	**0.001**	**0.000**	0.001
Greece	0.002	0.002	**0.002**	0.000	0.006	**0.000**	**0.003**	0.000	0.004
Hungary	0.004	0.004	**0.004**	0.005	0.005	0.004	**0.005**	**0.003**	0.006
Iceland	0.005	0.004	**0.004**	0.004	0.004	**0.002**	**0.002**	0.008	0.022
Ireland	0.003	0.004	**0.004**	0.003	0.004	**0.002**	**0.002**	0.008	0.022
Israel	0.004	0.003	**0.003**	0.004	0.006	0.004	0.007	**0.000**	**0.005**
Italy	0.002	**0.001**	0.001	0.002	0.003	0.001	0.002	**0.000**	**0.001**
Japan	0.002	0.002	**0.002**	0.001	0.002	**0.000**	**0.001**	0.002	0.004
Korea	0.002	0.001	**0.001**	0.003	0.003	0.002	0.003	**0.001**	**0.002**
Latvia	0.006	0.006	**0.005**	0.000	0.005	**0.000**	**0.005**	0.004	0.009
Luxembourg	0.002	**0.001**	0.002	0.000	0.002	**0.000**	**0.001**	0.002	0.002
Mexico	0.002	0.002	**0.009**	0.003	0.003	**0.003**	**0.003**	0.003	0.004
Netherlands	0.002	**0.002**	0.002	0.004	0.004	**0.003**	**0.003**	0.003	0.004
New Zealand	0.002	**0.001**	0.001	0.004	0.003	**0.000**	**0.001**	0.000	0.004
Norway	0.002	0.002	0.002	0.000	0.002	**0.002**	**0.003**	0.004	0.005
Poland	0.003	**0.002**	0.003	0.003	0.005	**0.000**	**0.004**	0.004	0.005
Portugal	0.003	0.002	**0.002**	0.000	0.004	**0.000**	**0.002**	0.000	0.002
Slovakia	0.005	0.005	**0.005**	0.006	0.006	0.005	0.006	**0.001**	**0.002**
Slovenia	0.004	0.003	**0.003**	0.000	0.005	**0.000**	**0.002**	0.000	0.002

Spain	0.002	0.004	**0.002**	0.000	0.006	0.000	0.003	**0.000**	**0.002**
Sweden	0.002	0.002	**0.002**	0.000	0.001	**0.000**	**0.001**	0.000	0.002
Switzerland	0.002	0.002	**0.001**	0.002	0.003	**0.000**	**0.001**	0.000	0.001
Turkey	0.016	**0.012**	0.013	0.006	0.008	**0.006**	**0.011**	0.018	0.023
UK	0.003	0.002	**0.001**	0.000	0.002	**0.001**	**0.001**	0.001	0.002
USA	0.003	0.002	**0.002**	0.003	0.003	**0.000**	**0.001**	0.000	0.005

Note: ARMSE denotes adjusted root mean square error while k is the kth period ahead forecast.

5. Conclusions

In this paper, we revisit the Salisu et al. (2017) in order to evaluate the out-of-sample forecast performance of their model. In essence, we employ the augmented Phillips curve expressed in a non-linear autoregressive distributed lag (NARDL) model as in Salisu et al. (2017). For the purpose of robustness and in line with the tradition in the literature, we also compare the forecast performance of the NARDL with the autoregressive model. Results for OECD countries suggest that the inclusion of asymmetries in the predictive model for oil price-inflation nexus does little to improve the out-of-sample forecast. We find evidence that accounting for asymmetries provides better in-sample inflation forecasts as in Salisu et al. (2017) while more accurate out-of-sample forecasts come from the symmetric model variants. The NARDL model also out-performs the autoregressive model. The finding has implications for the choice of framework for modelling and forecasting Phillips curve-based inflation.

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